STUDY ON THE PERFORMANCE OF DEEP LEARNING TECHNIQUES FOR THE CLASSIFICATION OF PARKINSON'S DISEASES

SYNOPSIS

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1. INTRODUCTION

Machine Learning and deep learning are promising technologies that may assist and support clinicians in providing an objective and reliable diagnosis of the disease based upon significant and unique features identified from relevant medical data. These models have proven to be very promising and can potentially outperform human graders. Parkinson's disease (PD) is a neurodegenerative disorder that affects dopaminergic neurons in the substantia nigra region of the brain [1-2]. People with PD may experience several symptoms including bradykinesia, dysarthria, anxiety, depression, sleep behavior disorders, and cognitive impairment [2-4].

PD may include both motor and non-motor symptoms that can make it difficult for affected patients to live normally [5]. Recent studies have also discovered relationships between risk alleles counts and health and the probability of developing PD [6]. In early stage of this disease, vocal impairments are commonly faced by PD patients [7]. So, on recent PD detection studies, vocal disorders-based diagnosis system is focused a lot and in deep learning, there will be a use of feature dimension reduction [8]. In classification of PD, commonly used algorithms such as L_1-Norm Support Vector Machine (SVM), Kernel-Based Extreme Learning Machine (KELM), Artificial Neural Network (ANN), K-Nearest Neighbor (KNN) and Random Forest (RF) methods gives lower performance due to irrelevant features, higher dimensionality in the dataset.

The main goal of this research work is to implement the framework by using accurate and reliable deep Learning techniques for PD detection. Thus, ensemble learning has been described for feature selection, and classification based on aggregation function. Ensemble learning evaluates a variety of approaches instead of single algorithms, and final results are generated by merging outputs of methods. This work focus on dimensionality reduction, Optimization Based Ensemble Feature Selection (OBEFS) algorithm, and Ensemble Deep Learning (EDL) has been proposed for feature selection, and classification based on the consensus function.

2. LITERATURE SURVEY

Cai et al [9] proposed an enhanced Fuzzy K-Nearest Neighbour (FKNN) method for the early detection of PD based upon vocal measurements. The proposed method, an evolutionary instance-based learning approach termed CBFO-FKNN, was developed by coupling the Chaotic Bacterial Foraging Optimization (CBFO) with Gauss mutation approach with FKNN. It has a very good prospect, which will bring great convenience to the clinicians to make a better decision in the clinical diagnosis.

Haq et al [10] predicted PD by implementing L1-norm Support Vector Machine (SVM) model. But, this work doesn't involve any dimensionality reduction before classification, so, it enhances the PD classifier computation time. Patra et al [11] employed Machine Learning (ML) classifiers to assess voices of patient datasets and identify PD. The study's base classifiers were Decision Tree (DT), Logistic Regression (LR), and KNN which had their performances compared to Ensembles like Bagging, Random Forest (RF), and Boosts. Results found out the most relevant features associated with the classification and ranked them based on feature importance.

Kaur et al [12] proposed a specific framework based on grid search optimization to develop an optimized deep learning Model to predict the early onset of PD whereby multiple hyper parameters are to be set and tuned for evaluation of the deep learning model. An innovative deep-learning technique is introduced by Wang et al [13] to early uncover whether an individual is affected with PD or not based on premotor features. The vocal features of PD affected individuals are analyzed by Xiong and Lu [14] with sophisticated computational models. Then the predictor candidate subset is identified from the processed vocal features using the Adaptive Grey Wolf Optimization (AGWO) algorithm, a meta-heuristic global search optimization technique. Furthermore, the latent representation of the candidate features is extracted through sparse auto encoders for effective discrimination between the PD affected and control cases.

Xia et al [15] proposed a dual-modal deep-learning-based model, where left and right gait is modelled separately by a Convolutional Neural Network (CNN) followed by an attention-enhanced Long Short-Term Memory (LSTM) network. Yu et al [16] proposed the speech recognition model for PD Patients Using Transfer Learning Technique (PSTL), where pre-trained the LSTM model. It is accurate, robust to voice features, and fast classification techniques based on deep learning method that can be used in practical PD detection systems.

3. PROBLEM DEFINITION

Parkinson's disease is a serious neurodegenerative disorder. It is reported that most of PD patients have voice impairments and are not perceptible to common listeners. Therefore, different machine learning methods have been developed for automated Parkinson's disease detection. However, these methods either lake generalization and clinically significant classification performance or face the problem of subject overlap. In this work LSTM based CNN classifier is proposed in addition with dimensionality reduction and feature classification technique. The proposed work is compared with the existing ML and CNN algorithms. Finally, the classification is performed between the Parkinson's patients and healthy people.

4. OBJECTIVES OF THE RESEARCH

The major objectives of this research work to design a novel approach for effective PD diagnosis are discussed as follows,

- To classify between the Parkinsons's diseases patients and the healthy people Fuzzy Convolution Long Short-Term Memory Based Convolutional Neural Network (FCLSTM-CNN) technique is introduced with Feature selection technique by adapting Kernel Based Principal Component Analysis.
- To optimize the features using Fuzzy Monarch Butterfly Optimization algorithm and to classify between the affected people and the normal people Fuzzy Convolution Bi-Directional Long Short-Term Memory (FCBi-LSTM) classifier is used with the dimensionality reduction technique.
- To apply Optimization Based Ensemble Feature Selection Algorithm and deep learning classifier for Parkinson's disease detection.

- To detect the Parkinson's Disease accurately and to improve the detection rate, Ensemble Deep Learning (EDL) classifier is introduced with stacked generalization.

5. RESEARCH METHODOLOGIES

The experiments were conducted with PD dataset from University of California-Irvine (UCI) Machine Learning repository. In Cerrahpasa Faculty of Medicine, Istanbul University, at Neurology Department, gathered this dataset and it has 64 healthy individuals of 41

women and 23 men and 188 PD patients of 81women and 107men. Age of healthy patient's lies between 41 to 82years, while age of PD patients lies between 33 to 87. Microphone's frequency response was set at 44.1 KHz during data collection and after doctor's review, vowel /a/letter's repeated repetition in every person is collected with three replicates. These existing classifiers and proposed classifier have been implemented using MATLAB R2016a on recognising PD and classifying them. The following system requirements were followed during implementation: Intel(R) Core™i3-4160T CPU@3.10 GHz 3.09 GHz processor, 4.00 GB RAM, Windows 8.1 pro, 64-bit operating system, operation system, and 1 TB hard disk.

5.1. Kernel Based Principal Component Analysis Based Dimensionality Reduction and FCLSTM-CNN for Parkinson's disease Classification

In this phase, firstly features like Baseline features, Time frequency Features, Mel-Frequency Cepstral Coefficient (MFCC), Wavelet Transform (WT), Tunable Q-factor Wavelet Transform (TQWT), and Vocal fold features have been extracted from the dataset. Kernel based Principal Component Analysis (KPCA) dimensionality algorithm is introduced which reduces the dimension from a given dataset before it is fed to a PD classification. Pre-processed and labelled feature vectors were served as inputs to the KPCA algorithm. Then important features were selected using Minimum Redundancy Maximum Relevance (mRMR) feature selection technique. mRMR selects the features with high relevance scores with respect to class labels, while eliminating redundant features. Feature sets were given as input to FCLSTM-CNN. FCLSTM-CNN classifier, the fuzzy weight is computed via the membership function and adjusts the features response to extract the most relevant features of the predicted features. KPCA improves the overall performance of the model because it addresses the problem of overfitting in classifiers. Thus, optimal selection of features from the dataset still becomes an unsolvable issue, it can be solved by the next phase of the work.

5.2. FMBOA feature selection and deep learning classifier for Parkinson's disease

In this phase, KPCA based dimensionality technique, and FMBOA based algorithm is introduced for selecting the feature sets. FMBOA algorithm has been shown to obtain good results in terms of classification accuracy when it is used mostly without modification and this reflects the fact that there is a balance between global and local search in this algorithm. In this work, the global search attribute of the MBOA algorithm was modified in order to achieve more precise results and to improve its efficiency in finding the correct features from the start and before turning to local search. From the selected features, Fuzzy Convolution Bi-Directional Long Short-Term Memory (FCBi-LSTM) classifier is introduced for

classification. Bi-LSTM is used to encode selected features of PD samples into vectors, and produces class labels. Fuzzy weights are computed via the Gaussian Membership function. The single feature selection methods can have specific biases, whereas an ensemble features selection has the advantage to improve and compensate for these biases.

5.3. Optimization Based Ensemble Feature Selection Algorithm and deep learning classifier for Parkinson's disease

In this phase, Optimization Based Ensemble Feature Selection (OBEFS) algorithm has been proposed to select features based on the consensus. Ensembles of feature selection methods attempt to combine multiple feature selection methods such as FMBOA, LFCSA, and AFA. CSA strategy is used with the aim of escaping from the parental investment in raising their offspring and minimizing the risk of egg loss (irrelevant features) to other species. In the CSA, random search performed is able to be executed more capably with using Lévy flights. In AFA, iteration step of each firefly is self-adaptive which is determined by the difference between its current fitness value and the best fitness value of the population. The optimal features selected through OBEFS are used to train an FCBi-LSTM classifier. It is an effective and accurate model for properly diagnosing the condition at an early stage, which might help doctors aid in the cure and recovery of PD patients. Ensemble classification has been replaced by next phase to increase the results of the classification algorithm.

5.4. Ensemble Feature Selection and Ensemble Deep Learning (EDL) classifier for Parkinson's disease

In this phase, OBEFS and Ensemble Deep Learning (EDL) classification are introduced for identifying PD in patients. KPCA is introduced for dimensionality reduction followed by OBEFS. The proposed OBEFS algorithm is performed depending on FMBOA, LFCSA, and AFA. EDL classifiers such as FCBi-LSTM, Contractive Auto-encoder (CAE), and Sparse Auto-encoder (SAE) are used in classification. SAE method, drives AE more correctly to replicate inputs x without over fits. CAE uses the encoder function to map input data. The decoder functions are then used to map output class via the encoder activation function. EDL classifier combines the benefits of three deep learning models by aggregates their results using stacked generalization to provide a model with improved generalisation performance. Finally, the resultant outputs are evaluated with performance metrics.

6. EXPERIMENTAL RESULTS AND DISCUSSIONS

Experimental finding of the proposed EDL classifier and its comparisons with other approaches are discussed in this section. To analyse prediction performances of classifiers, evaluation metrics like F-measure, MCC, accuracy, and error rate were computed, and it has been discussed as below,

$$Precision = \frac{TP}{FP+TP} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$F - measure = \frac{2*(Recall * Precision)}{(Recall + Precision)} \quad (3)$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (4)$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (5)$$

$$Error\ rate = \frac{FP+FN}{TP+TN+FP+FN} \quad (6)$$

True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN) have been used to measure the above-mentioned metrics. The combination of MFCC + Wavelet + Concat features with a CNN classifier yields an accuracy rating of 94.1752 %. Despite the fact that the accuracy percentage of the MFCC + Wavelet +Concat combination is 95.1557% for the FCLSTM-CNN classifier, FCBi-LSTM classifier has 96.6381%, 98.0244%, 97.3457% and 98.7720% for TQWT+MFCC+Wavelet, TQWT+Wavelet+Concat, TQWT+MFCC+Concat, & MFCC+Wavelet Concat accuracy results respectively. Proposed EDL classifier with MFCC + Wavelet + Concat combination achieves the highest accuracy rate of 99.903%, F-Measure rate of 99.633%, and 72.431% for MCC (See Table 1).

TABLE 1. RESULTS OF CLASSIFIERS WITH TRIPLE FEATURE (KPCA+ OBEFS)

CNN CLASSIFIER (%)				
FEATURE COMBINATION	**F-MEASURE**	**ACCURACY**	**ERROR RATE**	**MCC**
F1-TQWT+MFCC+Wavelet	85.8697	87.5696	12.4304	57.2007
F2-TQWT+MFCC+Concat	90.2315	91.9315	8.0684	61.4600
F3-TQWT+ Wavelet + Concat	86.3695	88.0694	11.9306	63.3994

F4-MFCC + Wavelet + Concat	92.4752	94.1752	5.8248	64.5384
FCLSTM-CNN CLASSIFIER (%)				
FEATURE COMBINATION	**F-MEASURE**	**ACCURACY**	**ERROR RATE**	**MCC**
F1-TQWT+MFCC+Wavelet	94.2258	93.0470	6.9530	67.6669
F2-TQWT+MFCC+Concat	91.5250	93.0854	6.9146	67.7060
F3-TQWT+ Wavelet + Concat	93.4200	93.1261	6.8739	65.4457
F4-MFCC + Wavelet + Concat	91.6921	95.1557	4.8443	67.2960
FCBi-LSTM CLASSIFIER (%)				
FEATURE COMBINATION	**F-MEASURE**	**ACCURACY**	**ERROR RATE**	**MCC**
F1-TQWT+MFCC+Wavelet	98.3100	96.6381	3.3619	74.300
F2-TQWT+MFCC+Concat	96.5900	98.0244	1.9756	72.300
F3-TQWT+ Wavelet + Concat	97.5200	97.3457	2.6543	70.300
F4-MFCC + Wavelet + Concat	98.5010	98.7720	1.2280	71.400
EDL CLASSIFIER (%)				
FEATURE COMBINATION	**F-MEASURE**	**ACCURACY**	**ERROR RATE**	**MCC**
F1-TQWT+MFCC+Wavelet	99.449	97.771	2.2299	75.432
F2-TQWT+MFCC+Concat	97.722	99.156	0.8436	73.412
F3-TQWT+ Wavelet + Concat	98.652	98.378	1.6222	71.013
F4-MFCC + Wavelet + Concat	99.633	99.903	0.0966	72.431

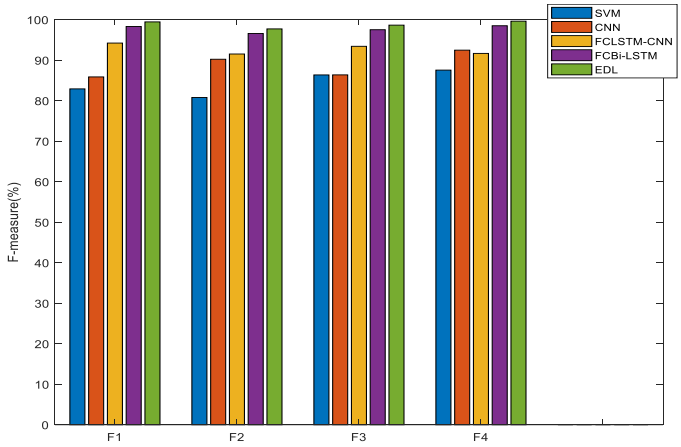

FIGURE 1. F-MEASURE COMPARISON OF FEATURE LEVEL COMBINATION VS. CLASSIFIERS

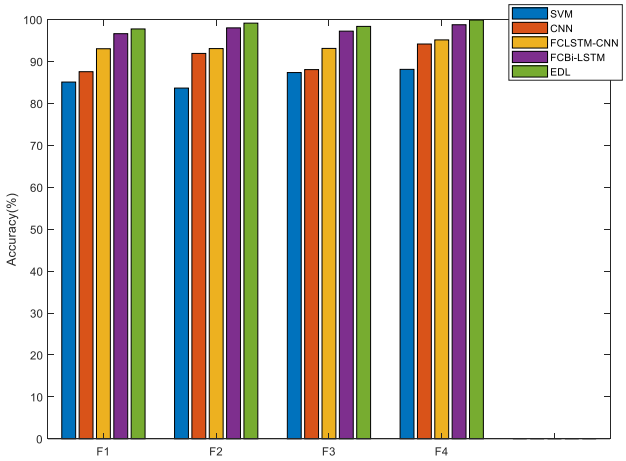

FIGURE 2. ACCURACY COMPARISON OF FEATURE LEVEL COMBINATION VS. CLASSIFIERS

Figures 1 shows f-measure comparison of feature combination sets with classifiers. From the results it concludes that the TQWT+MFCC+Wavelet feature set yields greater results of 99.449 %, 97.77 %, 75.432 %, and 2.2299 %for f-measure, accuracy, MCC, and error. The proposed EDL classifier using the first feature level combination achieves a higher f-measure of 99.449%, methods like CNN, FCLSTM-CNN, and FCBi-LSTM achieve f-measures of 85.8697%, 94.2258 %, and 98.3100%, respectively. Figure 2 shows that the x-axis results are measured using a feature-level combination of classifiers, and the y-axis results are shown as accuracy. The final feature level combination by EDL classifier achieves 99.9030% accuracy, methods like CNN, FCLSTM-CNN, and FCBi-LSTM achieve 94.1752%, 95.1557%, and 98.7720% accuracy, respectively.

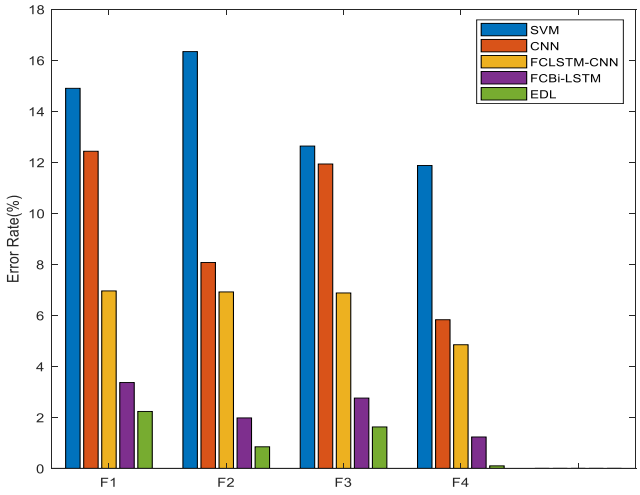

FIGURE 3. ERROR RATE COMPARISON OF FEATURE LEVEL COMBINATION VS. CLASSIFIERS

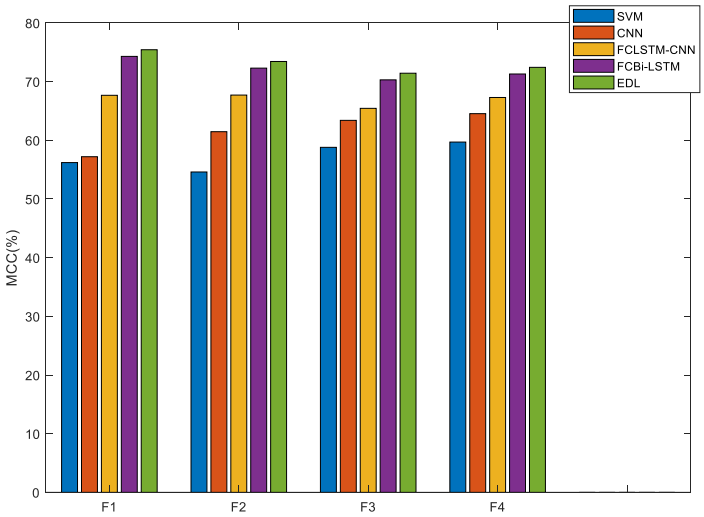

FIGURE 4. MCC COMPARISON OF FEATURE LEVEL COMBINATION VS. CLASSIFIERS

Figure 3 demonstrate that final feature level by EDL classifier yields a reduced error rate of 0.0966%, methods like CNN, FCLSTM-CNN, and FCBi-LSTM classifier exhibits a higher error rate of 5.8248%, 4.8443%, and 1.2280%, correspondingly. Figure 4 shows the comparison analysis in terms of MCC achieved with the first feature level combination yielding improved results of 75.432% for EDL classifier, and CNN, FCLSTM-CNN, and FCBi-LSTM techniques yield 57.2007%, 67.6669%, and 74.300% respectively.

7. CONCLUSION

Deep Learning (DL) method for clinical database has been developed that examine the scope of DL based models that are trained with the feasible feature subset of PD dataset for enhanced classification. KPCA is used for reducing the dimensionality of extracted

features. Then mRMR, FMBOA, LFCSA, AFA, and OBEFS algorithm is used for selecting important features from entire features set. OBEFS algorithm is introduced to next work for increasing the performance of the system. Correlation function is used to perform OBEFS in order to select optimal features from the three feature subsets. Then FCLSTM-CNN, FCBi-LSTM classifier, EDL classifier (FCBi-LSTM, CAE, and SAE) is introduced to PD diagnosis. In EDL classifier, stacked generalization was introduced to combine the results of classifiers. The results proved that the proposed system has higher results of accuracy, and lower error than the other existing approaches.

8. ORGANIZATION OF THE THESIS

Chapter 1 describes the detailed information about the deep learning, Feature Selection, ensemble modelling, problem definition, research work, and contribution of this research work. **Chapter 2** studies and analyses the literature surveys which are related to this research work. **Chapter 3** explains the first contribution of research work such as Kernel based Principal Component Analysis (KPCA), and FCLSTM-CNN for PD. **Chapter 4** describes the second contribution of the research work such as mRMR, and FCLSTM-CNN classification for PD. **Chapter 5** presents the third contribution of the research such as OBEFS via FMBOA, LFCSA, and AFA, FCBi-LSTM classifier to reduce the speed up the convergence. **Chapter 6** describes the fourth contribution of the research such as OBEFS and Ensemble Deep Learning (EDL) classification schemes are introduced for identifying PD in patients. EDL classifiers such as FCBi-LSTM, Contractive Auto-encoder (CAE), and Sparse Auto-encoder (SAE) are used in classification. **Chapter 7** explains the complete performance analysis of the proposed methods. **Chapter 8** concludes the research work and provides the possibility of future work for further development.

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List of Publications:

B. Sabeena Dr.S. Sivakumari Implementation of Feature Selection and Ensemble Deep Learning Classifier for Parkinson's disease "*Oxidation Communications" Volume no: 45 No 4, pp.701-713 December2022* (Scopus indexed).

B. Sabeena Dr.S. Sivakumari Ensemble Feature Selection and Ensemble Deep Learning Classifier for Parkinson's disease "*Journal of Theoretical and Applied Information Technology" Vol.101.no, pp.3416-3430 May 2023* (Scopus indexed).

List Of Conferences Attended:

Sabeena.B, Dr.S. Sivakumari, Dr.P. Amudha participated and presented a paper titled "A Technical Review on Various Approaches for Parkinson's Disease Classification" in International Conference on Modern Engineering, Science and Technology held on 17th February2020 at Ooty, Tamilnadu organized by Dr. Kalam Institute of Engineering Research, Chennai.

Sabeena.B, Dr.S. Sivakumari, Dr.P. Amudha participated and Presented a Paper title "Kernel based Principal Component Analysis based Dimensionality Reduction and Fuzzy Convolution Long Short-term Memory based Convolutional Neural Network (FCLSTM-CNN) for Parkinson's Diseases Classification "on April 9th and 10th in the International Conference in Eashwar College of Engineering 2021.

Sabeena.B, Dr.S. Sivakumari participated and presented a paper title "A Fuzzy Based Optimization Approach and a Deep Learning Classifier for Parkinson's Disease Prediction" 7th International Conference on Engineering Research and Innovations (ICERI-2022) Terna Engineering College (TEC), Nerul, Navi Mumbai.